Reference-less MR Thermometry Using Iteratively-Reweighted L_1 Regression

W. A. Grissom[1], M. Lustig[2], V. Rieke[3], A. B. Holbrook[3,4], J. B. Pauly[2], and K. B. Butts-Pauly[3]

[1]Electrical Engineering and Radiology, Stanford University, Stanford, CA, United States, [2]Electrical Engineering, Stanford University, Stanford, CA, United States, [3]Radiology, Stanford University, Stanford, CA, United States, [4]Bioengineering, Stanford University, Stanford, CA, United States

Introduction

Proton resonance frequency- (PRF-) shift MR thermometry is a promising tool for monitoring thermal therapies. In PRF-shift thermometry, maps of relative temperature changes are estimated by subtracting image phase in a pretreatment (baseline) state from image phase in a heated state. Baseline phase can be obtained from a pretreatment image, however, this approach is sensitive to motion and reduces SNR by $\sqrt{2}$. Reference-less thermometry methods [1,2] avoid these issues by estimating temperature from a single image via least-squares (L_2) polynomial regression and extrapolation. To avoid temperature misestimation, current reference-less methods require that the hot spot be masked out of the polynomial regression. This complicates their application, since the user must either know a priori the location of the hot spot, or employ a sophisticated tracking algorithm to follow it [3]. We propose a new reference-less thermometry method that uses robust regression so that the hot spot need not be masked out. The method therefore requires *no human interaction or tracking* to obtain accurate temperature maps, and is inherently robust to motion.

Theory

Reference-less thermometry methods assume that in the absence of therapy-induced temperature changes, image phase varies smoothly over space and can be accurately represented as a superposition of low-order polynomial basis functions, the coefficients of which are estimated via regression. In this context, the phases at spatial locations within the hot spot are regarded as outliers whose influence on the estimates is to be avoided. L_1 regression is a natural choice for this problem, since it is inherently robust to outliers. In our application, the L_1-optimal polynomial coefficients are given by:

$$\hat{\boldsymbol{a}} = \underset{\boldsymbol{a}}{\operatorname{argmin}} \sum_{n=1}^{N_s} \left| m_n \left(\theta_n - \{\boldsymbol{B}\boldsymbol{a}\}_n \right) \right|,$$

where $\boldsymbol{a}$ is a vector of polynomial coefficients, N_s is the number of spatial locations, m_n is the image magnitude, θ is the image phase, and $\boldsymbol{B}$ is the polynomial basis matrix. We solve this problem efficiently using an iteratively reweighted least-squares algorithm [5], so the computational burden is equivalent to solving a small number of L_2 regression problems.

To further enhance L_1 regression's robustness, we use an iteratively-reweighted L_1 regression algorithm [4] that solves a series of weighted L_1 regression problems:

$$\hat{\boldsymbol{a}}^l = \underset{\boldsymbol{a}}{\operatorname{argmin}} \sum_{n=1}^{N_s} \left| w_n^l m_n \left(\theta_n - \{\boldsymbol{B}\boldsymbol{a}\}_n \right) \right|,$$

where l is the current reweighting iteration. At each iteration l, the weights w_n^l are adjusted to downweight spatial locations with a large residual, such as the hot spot, thereby minimizing their influence on the estimated coefficients. This reweighting strategy improves upon L_1 regression's robustness to outliers, particularly when the hot spot becomes large.

Methods

We applied our method to a time series of images acquired during HIFU heating of a gel phantom. Heating was performed using an InSightec ExAblate 2000 HIFU system (Insightec Ltd., Tirat Carmel, Israel), and imaging was performed on a GE 3T Signa Excite Scanner (GE Healthcare, Waukesha, WI). The phantom was moved in and out of the scanner during heating. We applied the new method to the data, along with conventional L_2 reference-less thermometry *without* hot spot masking [1]. We also applied L_2 reference-less thermometry *with* hot spot masking by manually tracking the hot spot's center in each image. Figure 1 shows the experimental setup and the hot spot's trajectory.

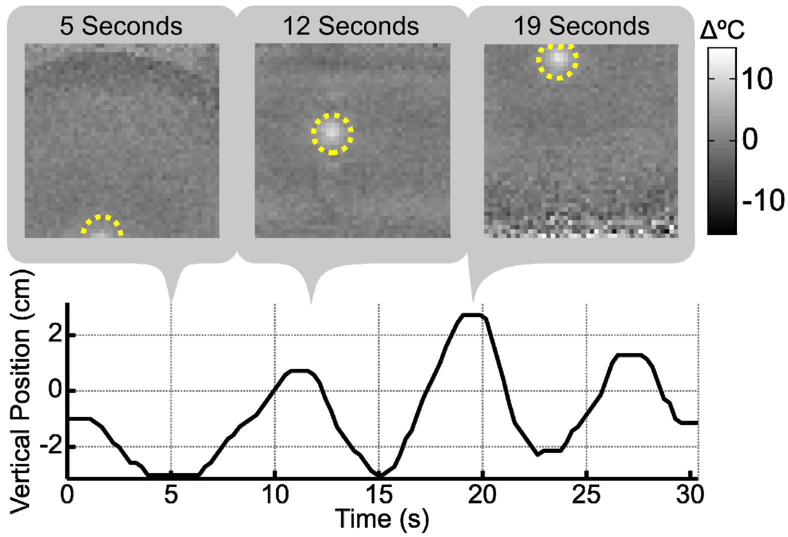

Fig. 1: Experimental Setup *The plot shows the location of the hot spot's center vs time. Temperature maps estimated with the reweighted-L_1 method are shown in the top row. Superimposed on these images is the boundary of the circular mask for the conventional L_2 method (dashed yellow line).*

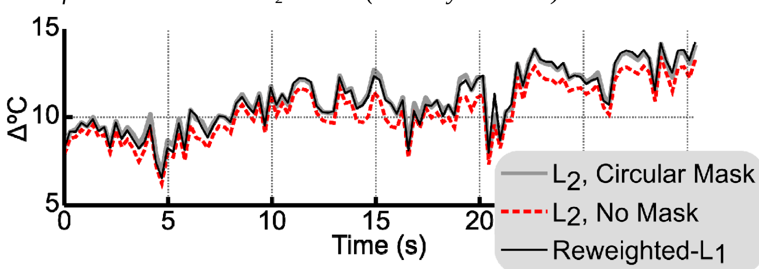

Fig. 2: Experimental Results *This plot shows that in the hot spot center, the reweighted-L_1 and the masked L_2 temperature estimates coincide, while the unmasked L_2 method underestimates the temperature rise due to bias.*

Results and Conclusion

Figure 2 shows that temperature estimates produced by the new method closely match those produced by the masked conventional method. The mean absolute deviation between the masked and unmasked conventional estimates was 0.72°C, while that between the masked conventional estimates and the reweighted-L_1 estimates was 0.15°C. These results demonstrate that the new method produces temperature estimates of similar quality to conventional reference-less thermometry, without requiring knowledge of the hot spot's location. Therefore, the new method represents an enhancement in robustness and usability over conventional reference-less thermometry.

Support NIH RO1 CA121163 **References** [1] V Rieke et al. MRM 51(6);1223-31, 2004. [2] K Kuroda et al. MRM 56(4);835-43, 2006. [3] D Kokuryo et al. Proc IEEE Conf Eng Med Biol Soc;2614-17, 2007. [4] E Candes et al. Tech Report, Caltech, 2007. [5] R Chartrand et al. IEEE ICASSP;3869-72, 2008.